SELECTION OF RISK RESPONSES FOR EFFICIENT CONTINGENCIES

Edouard Kujawski, Ph.D.^

Systems Engineering Department
Lawrence Berkeley National Laboratory
MS 46A-1123
Berkeley, California 94720
E-mail: e_kujawski@lbl.gov
Tel: 510-486-6932
Fax: 510-486-4711

September 2001

ABSTRACT

The primary goal of good project risk management should be to successfully deliver projects for the lowest cost at an acceptable level of risk. This requires the systematic development and implementation of a set of Risk Response Actions (RRA) that achieves the lowest total project cost for a given probability of success while meeting technical performance and schedule. This work presents a practical and mathematical sound approach for determining this "efficient RRA set". It is built on the portfolio selection concepts that Markowitz developed to determine the optimal investments for investors with differing aversions to risk. The set of RRAs is treated as whole and not just individual risks. Several conceptual and modeling differences are introduced to properly treat technical risks. The efficient RRA set is based on "Outcome Cost Vs Probability of Success" rather than "Expected return Vs Variance of return". The risks and RRAs are characterized using scenarios, decision trees, and cumulative probability distributions. The computations are performed using Monte Carlo simulation. The analysis provides information that enables decision-makers to select the efficient RRA set that explicitly takes their attitude toward risk and project risk into account. The computations are readily performed with commercially available tools such as Excel add-ins. The approach is detailed using a realistic but simplified case of a project with two independent risks.

Keywords: technical risk management, risk response actions, efficient set, probability of success, contingency, risk profile, risk trade-off, decision tree

^ This work was supported by the Director, Office of Science, Office of Basic Energy Sciences, Division of Engineering, of the US Department of Energy under Contract No. DE-AC03-76SF00098.

1. INTRODUCTION

In today's highly competitive environment and limited resources, the project manager[1] needs to (1) bid low enough to win the project but high enough to ensure that the project is a success, and (2) once the project is underway, judiciously manage the technical and managerial risks. Project risks can be categorized as technical and managerial; but the two are interrelated [Dillon and Paté-Cornell, 2001]. Technical risks are primarily associated with uncertainties in technology, performance, design, manufacturing, and integration. Managerial risks are associated with staff and management experience, inadequate schedule and budget, and programmatic issues. The unavailability of budget contingencies when needed results in schedule delays that further increase cost, scope changes, and/or project cancellation. It is no longer sufficient to just manage risk, the successful project manager must manage risk efficiently.

The present work focuses on the analysis and management of technical risks and presents an approach to balance risk, cost, performance, and schedule through the systematic development and implementation of Risk Response Actions (RRA). The selection of RRAs constitutes an important tradeoff between how much to invest in the RRAs versus the level of risk to be assumed [Hillson, 1999]. The proposed approach is designed to meet the following objective:

- Determine the set of RRAs that either (1) maximizes the probability of success for a given total project cost, or (2) minimizes the total project cost for a given probability of success.

We refer to such a solution as the "efficient RRA set." It has important implication for contingency management. If the RRA set is efficient, it is impossible to establish a smaller contingency without giving up some probability of success.

Numerous generic and statistical cost-risk models have been developed that use contingency factors [U.S. Department of Energy], cost estimating relationships [Parametric Estimating Handbook, 1999], and risk factors using the Analytical Hierarchy Process [Graham and Dechoretz, 1995]. These approaches provide a broad rather detailed view of project risks, and consequently they do not provide the technical project manager with adequate guidance for selecting an "efficient set of RRAs". Serious questions have also been raised about the domain of applicability of the AHP [Watson and Buede, 1987: 78]. Empirical studies [Shapira, 1995: 51] confirm that technical project managers want valid information rather than simplicity when making high-risk decisions. Chapman, Ward, and Bennell [2000] observe that decision-makers want "applied models that facilitate effective interventions" rather than inadequate theoretical models. The proposed approach by explicitly dealing with the RRAs and providing techniques for determining the efficient RRA set technically addresses these needs.

We build on the following Markowitz' basic "efficient portfolio selection" principles:
1. A good portfolio is more than a long list of good stocks and bonds. It is a balanced whole, providing the investor with protections and opportunities with respect to a wide range of contingencies [Markowitz, 1976: 3].

[1] The specific title of this role depends on the organization.

2. The security which is risky or conservative, appropriate or inappropriate, for one portfolio may be the opposite for another. One must think of selecting a portfolio as a whole, not securities *per se*.
3. The efficient portfolio provides the most suitable combination of risk and return [Markowitz, 1976: 7].
4. The proper choice among efficient portfolios depends on the willingness and ability of the investor to assume risk [Markowitz, 1976: 6].

These principles are powerful and apply to areas beyond portfolio selection. By simply changing the actors and objects, these principles transfer directly to project risk management.

But, we also need to modify some of Markowitz' techniques and introduce conceptual and modeling differences to properly treat technical risks. Specifically:

1. We define the efficient RRA set based on "Outcome Cost Vs Probability of Success" rather than "Expected return Vs Variance of return (E, V)".
2. The computation of the efficient RRA set requires evaluating discrete combinations of RRAs rather than the fraction invested in the jth security. We do not implement Markowitz' computing procedures [Markowitz, 1976: Chapter 8 and Appendix A]. We use Decision Trees (DT), Monte Carlo simulation, and cumulative risk profiles.
3. We assume that there is no correlation among the individual risks. This approximation avoids the complex and unfamiliar task of modeling factors that are common across a project and increase the tendency of some risks to move up and down together. The validity of the assumption depends on the application. It is not valid for security portfolios [Markowitz, 1976: 97]: "Covariances are essential to an analysis of efficient portfolios."

The proposed approach for determining an "efficient set of RRAs" offers the following benefits:

- It allows for explicit modeling of project outcomes using both discrete and continuous probability distributions.
- It provides complete information and visibility into the possible outcomes and selection of RRAs.
- It supports the decision-makers' attitude toward risk and how they make real decisions.
- It determines the lowest contingency cost required as a function of the assumed risk level.
- Technical project managers should find it both useful and practical for sound decision-making and optimization of project success.
- It can be implemented using commercial Excel® add-ins (@Risk®, Crystal Ball®, and Insight.xla®)[2] and/or more specialized tools such as DecisionPro®.

The content of the paper is as follows. In the Introduction we presented the rationale behind the proposed approach, some of Markowitz' portfolio selection principles, and how we propose to apply them to the analysis and management of technical risks. In Section 2 we describe the use of scenarios to elicit risk information and risk profiles to characterize risk. In Section 3 we present the modeling and analysis of individual RRAs using the data from Section 2 as input. In Section 4 we build on Markowitz' efficient set and develop an analogous paradigm for the selection of RRAs. The concepts of Sections 2, 3, and 4 form the basis upon which we select an efficient set of RRAs and determine an optimal total project cost contingency. In Section 5 we extend and apply these ideas to projects with multiple risks. In Section 6 we summarize the implications of the proposed approach to the

[2] This list is representative and not exhaustive.

management of technical risks. The appendices provide additional details on modeling (Appendix A), the illustrative example (Appendix B), and a brief look at the mathematics of discrete distributions (Appendix C).

2. MATHEMATICAL MODELS FOR QUANTIFYING TECHNICAL RISK

2.1. Risk Profile

A full characterization of risk requires specifying the following four elements: the possible events, their probability of occurrence, the range of impacts or outcomes associated with each event, and the conditional probability of each outcome given that the event has realized [Chapman and Ward, 1996]. It can be graphically represented in multiple ways, and in this work we use the following representations (See Appendix A for details):

1. Standard event trees using discrete outcomes.
2. Modified event trees where probability distributions rather than discrete branches are associated with the chance nodes. This provides the capability way to model continuous outcomes.
3. Simulation models that can be readily implemented using commercially available tools (See Section 1).

2.2. Using Scenarios to Quantify Technical Risk Contributors

Scenarios [Chapman and Ward, 1996] provide a convenient technique to elicit the judgment of experts about probabilities and consequences of project technical risks. In the proposed method, we explicitly evaluate each risk contributor using three scenarios and a variation of the fractile method [Haimes, 1998] as follows:

1. Optimistic scenario or 20th percentile of outcomes - It represents a credible upside scenario with a perceived probability of 20% (one chance in five) that the outcome will be better. Statistically, it is the 20% lower-confidence interval on the outcome.
2. Pessimistic scenario or 80th percentile of outcomes - It represents a credible downside scenario with a perceived probability of 20% that the outcome will be worse. Statistically, it is the 80% lower-confidence interval on the outcome.
3. Most-likely scenario - This characterizes an intermediate outcome or range of intermediate outcomes with the highest perceived likelihood of happening or mode. This is often associated with the traditional point estimate.

We use the "one chance in five" outcomes because these values are not too extreme and their use in place of upper and lower bounds assists the domain expert by raising useful questions of what could go wrong with the project baseline. Different levels of probability could be used [Markowitz, 1976: 32]. By specifying three outcomes and associated probabilities, the experts are able to encode their level of confidence for the possible outcomes. This data can be reported either in tabular form or graphical form.

2.3.1 Discrete versus Continuous Probability Distributions

Cost and schedule exhibit a continuous range of outcomes. For this reason and possibly greater familiarity, analysts may opt to approximate the scenario data with continuous probability distributions. Depending on the statistical characteristics they want to capture, there is a multitude of ways to use a continuous probability distribution to approximate a three-point discrete distribution. Popular parameterizations include the triangular and beta distributions [Garvey, 2000].

2.3.1. The Standard Triangular Distribution

The standard triangular distribution elicits the lower, most-likely, and upper values of the variable from the domain expert. It does not explicitly solicit the experts' level of confidence in any of these values. Furthermore, the specification of upper and lower bounds for the range of possible outcomes rarely provides useful guidance for decision-making under risk. In contrast, the proposed scenario-based approach by eliciting the 20% and 80% confidence level values rather than extreme values captures the degree of belief and confidence of the experts. It also provides a framework for using beta distributions, if so desired.

2.3.2. The Beta Distribution

The beta distribution, denoted by Beta(α, β, a, b), is very attractive for use in risk analysis [Garvey, 2000]. It is defined over a finite range [a, b] with a shape characterized by two parameters α and β. Depending on the shape parameters it can assume a variety of both symmetrical and asymmetric shapes: uniform (α=β=1), bell-shaped (α, β > 1), U-shaped (α, β <1), right-skewed triangular (α=1, β=2), left-skewed triangular (α=2, β=1). The expert can select the distribution that best characterizes her state of knowledge for the variable under consideration. This removes some of the shortcomings of the standard triangular distribution method [Moran, 1999].

3. MODELING AND ANALYZING INDIVIDUAL RRAS

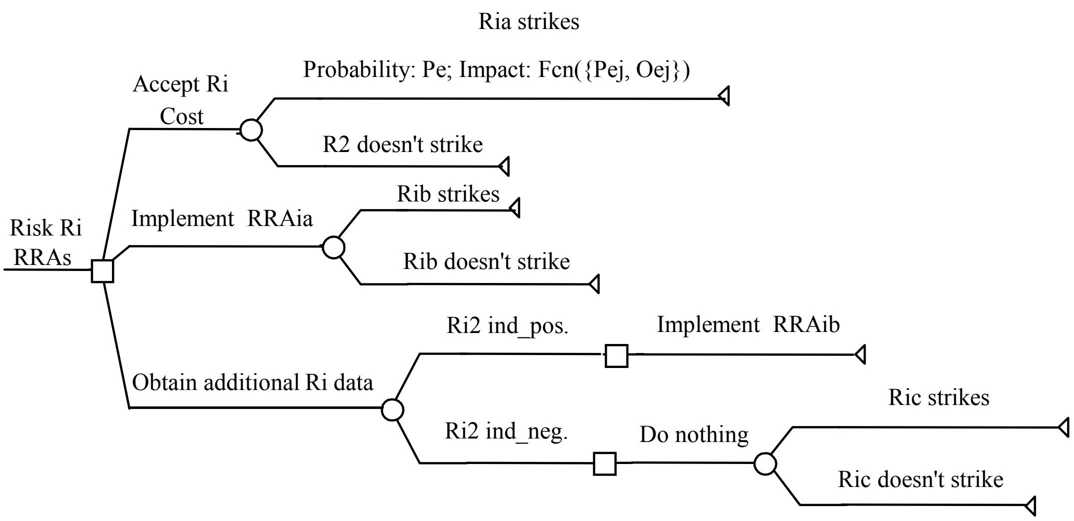
There are typically many possible RRAs to a particular source of risk [Hall, 1998]. We explicitly consider the following three generic RRAs:

1) **Accept the risk as is** - The project recognizes the existence of the risk but considers it acceptable to simply monitor it using the standard approach.
2) **Modify design** - The project immediately implements RRAs such as selecting an alternate design, modifying the scope, switching vendors, pursuing parallel paths, etc.
3) **Obtain additional information** - The project invests in additional analysis, testing, and/or prototyping before implementing costly RRAs. The RRAs are adapted and implemented as the situation evolves and information is acquired.

We use DTs as the framework for systematically developing and modeling the technical RRAs[3]. The resulting analysis introduces all of the concepts needed for modeling and analyzing risks involving additional and/or other types of RRAs.

3.1. The Basic RRA DT

We illustrate the approach by considering a single technical risk R1. The resulting generic DT, shown in Figure 4, lays out a simple architecture for developing and evaluating the RRAs for each individual risk. It also provides the basic template for dealing with multiple risks, as detailed in Section 5.



RRAj: Risk Response Action j
Pe: Probability of event e
Fcn: Conditional density probability distribution for outcomes given event e occurs

Figure 1. Basic RRA DT template.

Figure 1 follows the standard DT convention and the compact notation described in Appendix A. The three decision branches represent the three RRAs identified above. Each

[3] Note that, as discussed in Section 4, we do not use standard DT analysis for optimizing the RRAs.

chance branch may represent either a discrete or a continuous distribution of outcomes depending on the density probability distribution, Fcn.

3.2. Quantification of the Basic RRA DT

To proceed with the assessment of the RRAs, the parameters of the RRA DT in Figure 1 need to be quantified. This is a challenging task that requires experience, the ability to make educated guesses, and a healthy dose of common sense. The probabilities and consequences associated with the "Accept risk" and "Implement RRAa" options should be directly obtained from the domain experts as described in Section 2. The " Obtain additional data " parameters depend on the diagnostic capabilities of activities such as analysis, testing, and/or prototyping which, given finite resources, are not perfect. There is a tradeoff in deciding how much effort to expand on obtaining the additional information. A lower effort costs less, but it results in data that is less discriminating and a higher probability of a "false negative" that may result in severe consequences and higher costs later in the project. The data for the "Obtain additional data" RRA is determined using Bayes' Formula, as described in Appendix B.

3.2.1. Illustrative Example: Single-Risk Case

We quantify the parameters in the basic RRA DT (Figure 1) to reflect the following properties of realistic RRAs:

- There is a cost associated with each RRA.
- Practical RRAs are not 100% effective.
- There is a cost associated with each residual risk.
- The residual risks are less severe than the initial risks (lower probabilities for the severe consequence outcomes).

Figure 2 depicts the resulting mathematical model equivalent to the RRA DT in Figure 1. For ease of interpretation, each cell is identified with a self-descriptive label and its mathematical formula. The names of the branches have been abbreviated for legibility.

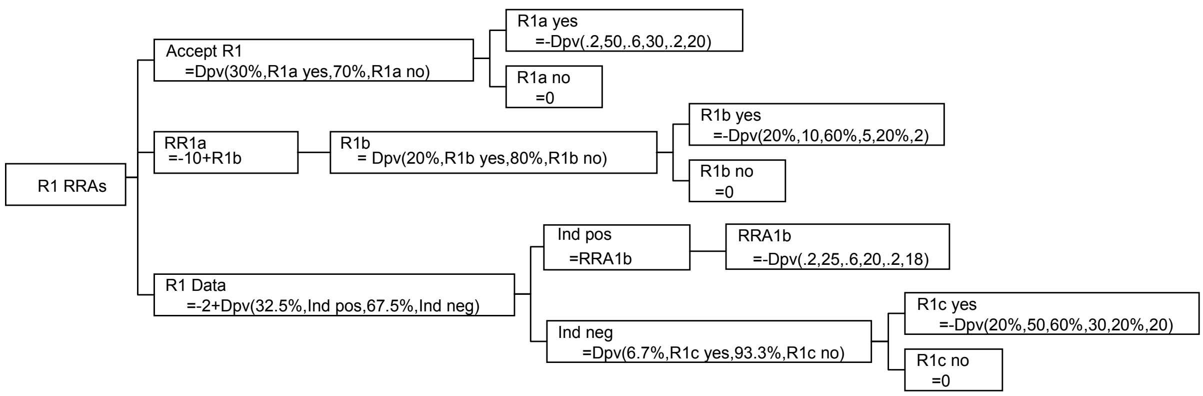


Figure 2. Mathematical Model of RRAs for a Risk R1.

For completeness and assistance to the interested reader, we provide the detailed quantified RRA DT in Appendix B, Figure B1. The choice of a representation is a matter of personal choice[4].

The mathematical model in Figure 2 has been evaluated using Monte Carlo simulation. The risk profiles and cumulative risk profiles for the individual RRAs are shown in Figures 3a and 3b, respectively. The cumulative risk profiles exhibit the step-behavior and multiple values for a given fractile characteristic of discrete distributions [Markowitz, 1976: 55]. Given that we are interested in real-world projects, it is reasonable to avoid this ambiguity by approximating the step-like cumulative risk profile by a monotonic function. For example, the curve "mono AR1" in Figure 3b is such an approximation to the curve "Accept R1. The differences can be made to be arbitrarily small and do not pose any practical limitations. The associated means and variances are compared in Figure 4. The reported results were obtained using Decision Pro®. Essentially identical results were obtained using other commercial tools[5].

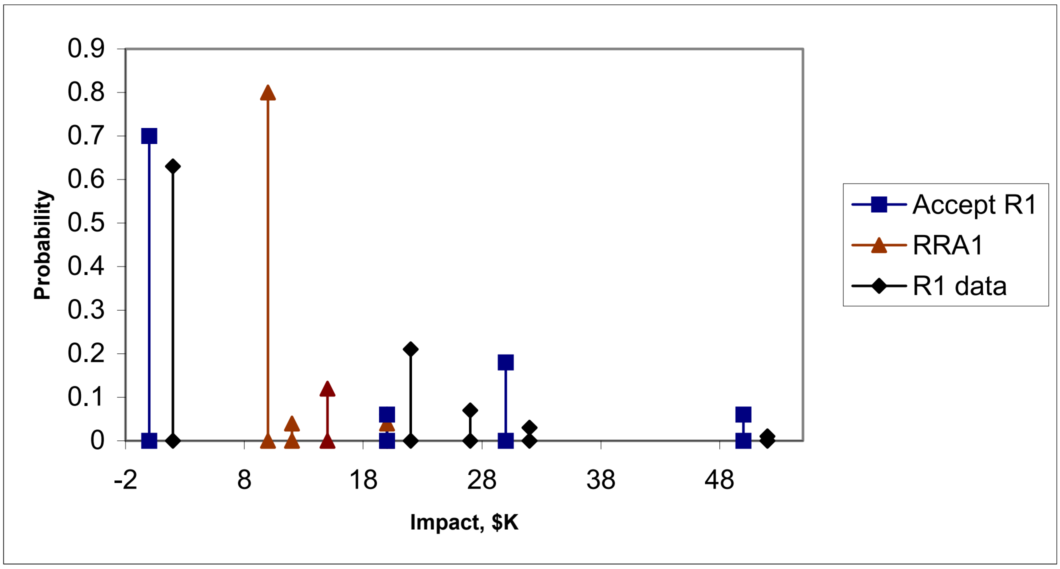


Figure 3a. Risk Profiles for candidate R1 RRAs.

[4] The author prefers the mathematical representation to emphasize that the processed decision process is not based on standard DT analysis.
[5] See Section 1.

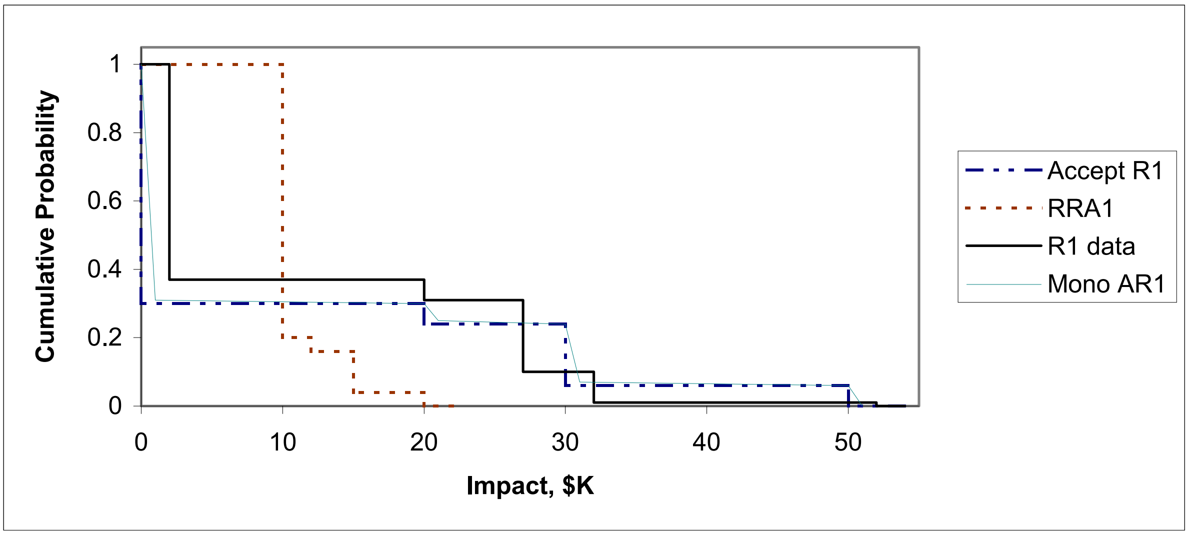


Figure 3b. Cumulative risk profiles for candidate R1 RRAs.

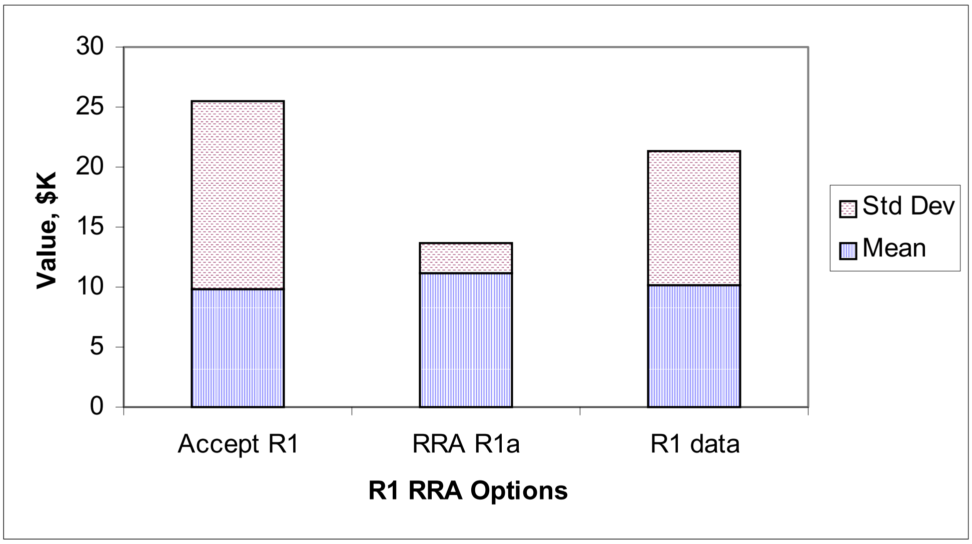


Figure 4. Means and standard deviations for candidate R1 RRAs.

4. DETERMINATION OF EFFICIENT RRA SET

The risk profiles and/or the risk cumulative risk profiles in Figures 3a and 3b provide complete information and visibility into the range and probability of the possible outcomes of each RRA. But mathematically assessing such data is quite complex, and it is an active research area in many different fields that range from economics to psychology [Kahneman, Slovic, and Tversky, 1999]. We now examine the applicability of several techniques for comparing risks and selecting an efficient RRA set. For illustration purposes we use the data in Section 3. There is no loss of generality because the cumulative risk profile characterizes risk whether made up of one or more individual risks. In the next section, we apply the proposed approach to multiple risks and the selection of an efficient RRA set on a project-wide basis.

4.1. Comparing Cumulative Risk Profiles

Each cumulative risk profile in Figure 3b provides the probability that the associated RRA does not exceed a given cost. For example, the "R1 data' RRA has a 63% probability of success at a cost of $2K and only a 0.9 % probability of costing $52K on the downside. Such data is very valuable because it provides the project manager with the information she needs to determine how much contingency should be available for a given confidence level or probability of success. The importance of such information is supported by empirical studies [Shapira, 1998] that show that the majority of technical project managers think that risk is not adequately characterized by its mean value but that it depends more on the magnitude of the downside distribution of outcomes than the probability.

The three cumulative risk profiles in Figure 3b cross each other. Intuitively, this means that no RRA ("Accept R1", "RRA1a", or "R1 Data") is preferred under all possible selection criteria. In the language of the field, none of these RRAs exhibits stochastic dominance [Chapman and Ward, 1997]. The "RRA1a" RRA provides the lowest cost approach for achieving a probability of success exceeding 80%. This cost ranges from $10K at 80% to $22K for essentially 100% probability of success. The two other RRA options cost more to provide the same probability of success. The "Accept R1" option provides a 70% probability of success for free; but, it carries significantly higher risks than the other two RRAs. The "R1 Data" RRA provides a more balanced approach between risk and a competitive bid. The preferred RRA depends on the decision-maker's attitude toward risk; but as we discuss below there is a preferred solution.

4.2. Developing the Efficient Contingency Frontier

We use Markowitz' "efficient portfolio selection principles"[6] to determine a preferred set of RRAs. We paraphrase these principles for technical risk management as follows:

1. A good set of RRAs is more than a long list of individual RRAs. It is a balanced whole, providing the project with protections and opportunities with respect to a wide range of contingencies.

[6] See Section 1

2. A RRA which is risky or conservative, appropriate or inappropriate, for one project may be the opposite for another. One must think of selecting the set of RRAs as a whole, not individual RRAs *per se*.
3. The efficient RRA set provides the most suitable combination of risk and return.

4. The proper choice among efficient portfolios depends on the willingness and ability of the project manager to assume risk.

Mathematically speaking, when selecting RRAs from the set of available RRAs there is a subset of RRAs that provides a given probability of success for the lowest cost. This set of RRAs determines the lowest contingency necessary to support the acceptable probability of success. Its composition changes with the probability of success. We refer to the resulting set of RRAs as the Efficient RRA Set (ERRAS) and the associated points as the Efficient Contingency Frontier, ECF.

In this section, we illustrate the development of the ECF for a single risk using the example in Section 3. Figure 5 depicts the three RRAs of Figure 3b and the associated ECF. The points that lie to the left of the ECF represent RRAs that bear a greater negative impact than necessary for a given probability. No RRA has a value or probability represented by a point below the ECF. To optimize winning the project and successfully carrying it out, project managers should specify the risk they are willing to take and then use the ECF to determine the contingency they need.

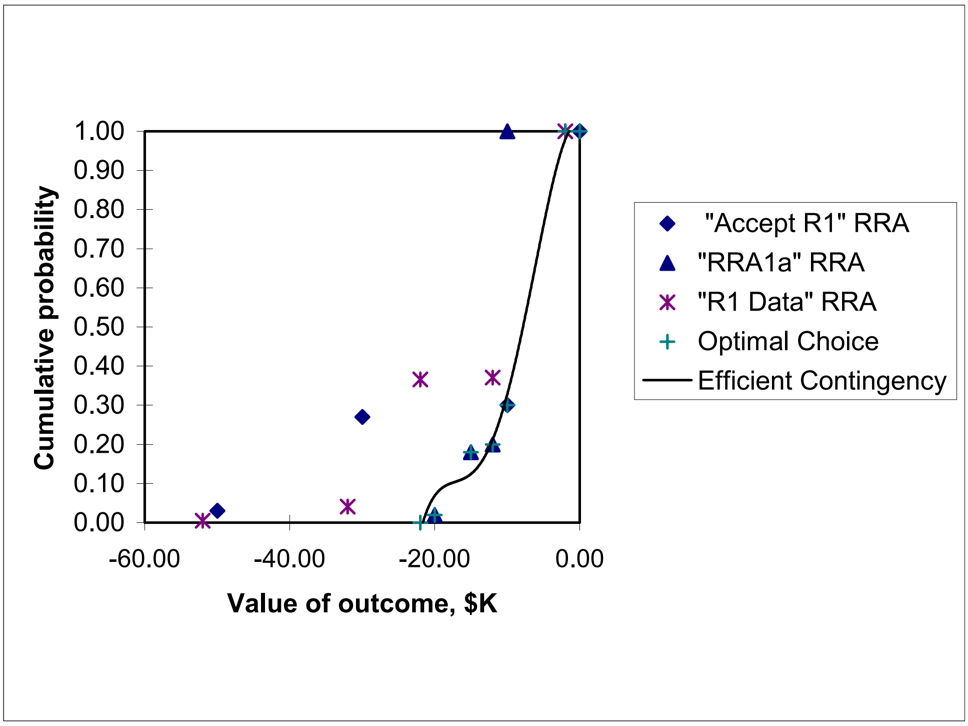


Figure 5. Determination of the Efficient Contingency Curve

4.3. Applicability of Simple Metrics

Financial stocks can be adequately characterized using a few key statistical parameters such as the mean and variance [Markowitz, 1976]. But there are significant differences between financial portfolios and technical project risks that may invalidate the use of identical metrics. Project cost and schedule risk profiles are typically highly skewed [Schragenheim and Dettmer, 2001]; applicable statistical data is rarely available; and the focus is on the downside of individual projects. Nevertheless, it would be attractive to be able to characterize technical risk using a few key parameters. We now examine several metrics for applicability to risk and contingency management.

4.3.1. Mean and Standard Deviation

Figure 4 depicts the means (μ) and standard deviations (σ) of the R1 RRAs. The "Accept R1" RRA has the smallest mean risk, -$9.0K, and the largest standard deviation, $14.6K. In contrast, the "RRA1a" RRA has the largest mean risk, -$11.0K, and the smallest standard deviation, $2.2K. Most technical project managers would agree that the "Accept R1" RRA represents a higher risk than the "RRA1a" RRA. The mean or the standard deviation, as standalones, are not appropriate measures of risk.

4.3.2. One-Standard-Deviation Value, $\mu-\sigma$

4.3.2.1. General Risk Distribution

For normal distributions the value ($\mu-\sigma$) has a cumulative probability P(Value <= $\mu - \sigma$) = 16%. When talking risk, this corresponds to a 84% probability of success. But for skewed distributions this probability needs to be explicitly calculated. For example, Figure 3b provides the following values for the R1 RRAs:

- The "Accept R1" RRA has a 27% probability of a cost greater than $24K, P(Value <- 24) = 27%.
- The "RRA1a" RRA has a 37% probability of a cost greater than $13K P(Value <-13) = 37%.
- The "R1 Data" RRA has a 20% probability of a cost greater than $20K P(Value <- 21) = 20%.

Based on the one-standard-deviation value, the "R1 Data" RRA is preferred to the "Accept R1" RRA[7]. But another discriminator is required to rank the "RRA1a" RRA. This example illustrates the need for caution when using the one-standard-deviation value as selection criterion since its use can be dangerous when dealing with skewed distributions.

4.3.2.2. Applicability of the Central Limit Theorem (CLT)

The CLT [Garvey, 2000: 186] states that " Under certain conditions, the sum of a large number of independent random variables approaches the normal distribution." The total risk is then approximately given by a normal distribution with a mean that is the sum of the individual means and a variance that is the sum of the individual variances. The one-standard-deviation value corresponds to an 84% probability of success and it provides a reasonable and practical approach for comparing risks and evaluating total project contingency.

The conditions of the CLT are often satisfied when dealing with multiple risks and total cost. The project-wide risk consisting of N independent risks with means μ_i and standard deviations σ_i is approximately given by a normal distribution with

[7] As specified, loss has a negative value and the more negative the value the greater the loss. If V1 < V2 then V1 corresponds to a greater loss than V2.

$$\mu = \Sigma\, \mu_i \quad \text{and} \quad \sigma^2 = \Sigma\, \sigma_i^2 \quad ,$$

where the sums range over i from 1 to N.

The value $(\mu - \sigma)$ corresponds to an 84% probability of success; i.e.

$$\text{Prob}(|\text{Loss}| < |\mu - \sigma|) = 84\% \ ,$$

where $|X|$ denotes the absolute value of X. The value for any probability of success α is simply given by

$$V_\alpha = \mu - z_\alpha * \sigma \ ,$$

where z_α is the z-value from the standard normal distribution [Shaikh, 1998].

When the CLT is applicable, it can be used to greatly simplify the computations. But, caution is required and the analysts should ensure that the assumptions are reasonable.

4.3.3. Other Metrics

Technical project managers who are highly risk-averse tend to focus or worst-case scenarios or select the option with the lowest risk at a high confidence level. The 95th percentile values (5% probability of a worse outcome) for the three RRAs in Figure 3b are as follows: ~ -$30K for the "Accept R1" RRA; ~ -$15K for the "RRA1a" RRA; and ~ -$22K for the "R1 Data" RRA. Based on this criterion, the "RRA1a" RRA is preferred. Comparing different risks using a single point on the cumulative risk profiles is not a robust method and does not provide a balanced consideration of all the possible outcomes.

Risk aversion is often modeled using a utility function. But, empirical studies indicate that most technical managers are unlikely to use such data for decision-making under risk/uncertainty. To quote [Shapira, 1995: 51]: "Ideally, it would be an advantage for managers if risk could be described in one number. However, acknowledging the many facets of risk, most felt that transforming a multidimensional phenomenon to one number might not be adequate or helpful."

4.4. Limitations of Standard DT Analysis

Standard DT analysis selects the decision branches with the highest or lowest expected value. Although each of the potential outcomes is explicitly modeled in the DT, this detailed information is lost when folding-back and averaging the data. The output is therefore inappropriate for selecting RRAs, where the preferred option may depend on the decision-maker's attitude towards risk. Theoretically, a utility function may be developed to addresses this concern. But as indicated above, this is not likely to be used by technical managers making for decision making under risk/uncertainty.

5. DEALING WITH MULTIPLE RISKS

We now build on the previous sections to deal with projects that face multiple risks and require the implementation of multiple RRAs. The objective is to determine the combination of RRAs that either (1) maximizes the probability of success for a given total project cost, or (2) minimizes the total project cost for a given probability of success. The Efficient Total Project RRA Set (ETPRRAS) includes multiple RRAs, and the Total Project ECF (TPECF) specifies the Total Project Cost Contingency (TPCC).

Formally, the problem can be stated as follows:
Given a project with multiple individual risks, R_i where (i= 1, …N), and associated RRAs, RRA_{ij} where (j =1,2,…,N for a given R_i), determine the combination of RRAs, $\{RRA_{1j}, RRA_{2k},\ldots,RRA_{Nl}\}$, that either (1) maximizes the probability of success for a given total project cost, or (2) minimizes the total project cost for a given probability of success.

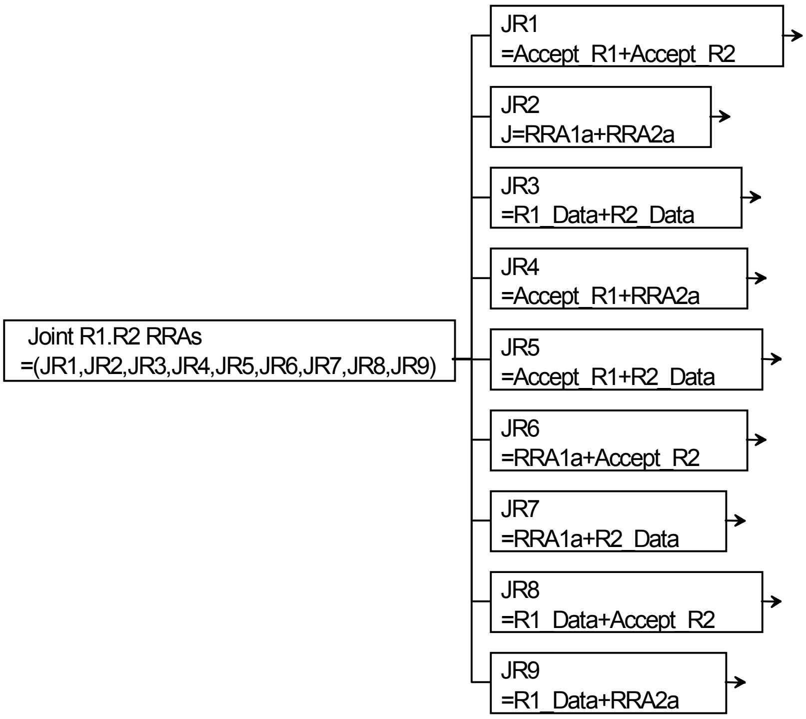
In Section 5.1 we first illustrate the approach using a concrete example of a project with two risks. The procedure is then generalized to determine the efficient RRA set for projects with any number of risks and RRAs.

5.1. Illustrative Example: Two-Risk Case

We illustrate the proposed approach and nature of the ETPRRAS by a small project with two technical risks, R1 and R2, and the following assumptions:

1. Risks R1 and R2 are statistically independent. There is no correlation between them.
2. The three generic RRAs defined in Section 3 are options for each risk.
3. The outcome values depend on the RRAs.
4. The outcome of R1 does not affect the outcome of R2 and vice versa.
5. The R1 data and R2 data are provided in Section 3 and Appendix B.2, respectively.

There are nine possible Total Project RRAs (TPRRA) given by the set of combinations $\{RRA_{1i}, RRA_{2j}\}$ where i and j =1,2,3 corresponding to the three possible individual RRAs (Accept R_i, RRA_i, R_i Data). The TPRRAs, denoted by JR_k where k=1,…,9, are mathematically modeled as shown in Figure 6.



⟶ : Pointers to individual RRAs

Figure 6. Mathematical model for the case of two risks

As depicted in Figure 6, the residual risk associated with each joint RRA is quantitatively given by a probability distribution that is the statistical sum of the contributing risk probability distributions. Since we assume that there is no correlation among the individual risks, these sums are routinely computed using Monte Carlo simulation that independently samples the individual distributions. Appendix C briefly outlines the calculus of discrete probability distributions [Kaplan, 1981] as another approach for solving and/or viewing the problem.

The techniques of Sections 2, 3 and 4 are directly applicable to the total project risk, as summarized below:

1. Each TPRRA in Figure 6 is characterized in terms a cumulative risk profile and associated statistics.
2. The composition of the ETPRRAS varies with the probability of success and defines the TPECF.
3. The TPECF determines the lowest TPCC for a given probability of success.

Table I summarizes a few key parameters including the mean, standard deviation, selected outcomes, and the TPECF. Figure 7 depicts the cumulative risk profiles on a common graph. Given the need for conciseness and the resulting crowded appearance, it is intended for illustration purposes rather than detail. In full size and color, the graphical representation provides artistic and interesting curves that capture the complexity of the risk profiles and provide information beyond the data in Table I. But as discussed below, the data in Table I is adequate to explicitly characterize and compare the various TPRRAs.

Table I. Summary Statistics for the Case of Two Risks

Total Project RRA		Cost $K						
						Probability of Success		
ID*	**Description**	**Mean**	**Std Dev**	**Min**	**Max**	**50%**	**80%**	**95%**
JR1	AR1.AR2	15.1	16.9	0.0	70.0	8.0	30.1	50.0
JR2	RR1.RR2	15.9	3.3	14.0	34.0	14.0	19.0	24.0
JR3	R1Data.R2Data	14.7	11.7	3.0	73.0	8.0	27.2	33.0
JR4	AR1.R2Data	14.2	16.0	1.0	71.0	6.0	31.0	51.0
JR5	AR1.RR2	14.4	15.9	4.0	64.0	4.0	34.4	54.0
JR6	RR1.AR2	16.6	6.8	10.0	40.0	17.0	19.8	30.0
JR7	RR1.R2data	15.7	4.3	11.0	41.0	16.0	17.6	24.0
JR8	R1Data.AR2	15.7	12.9	2.0	72.0	10.0	27.2	40.0
JR9	R1Data.RR2	15.0	11.3	6.0	66.0	6.0	26.0	31.0
	ECF	14.2	3.3	0.0	34.0	4.0	17.6	24.0
	ECF RRA	JR4	JR2	JR1	JR2	JR5	JR7	JR2, JR7

* Defined in Figure 6

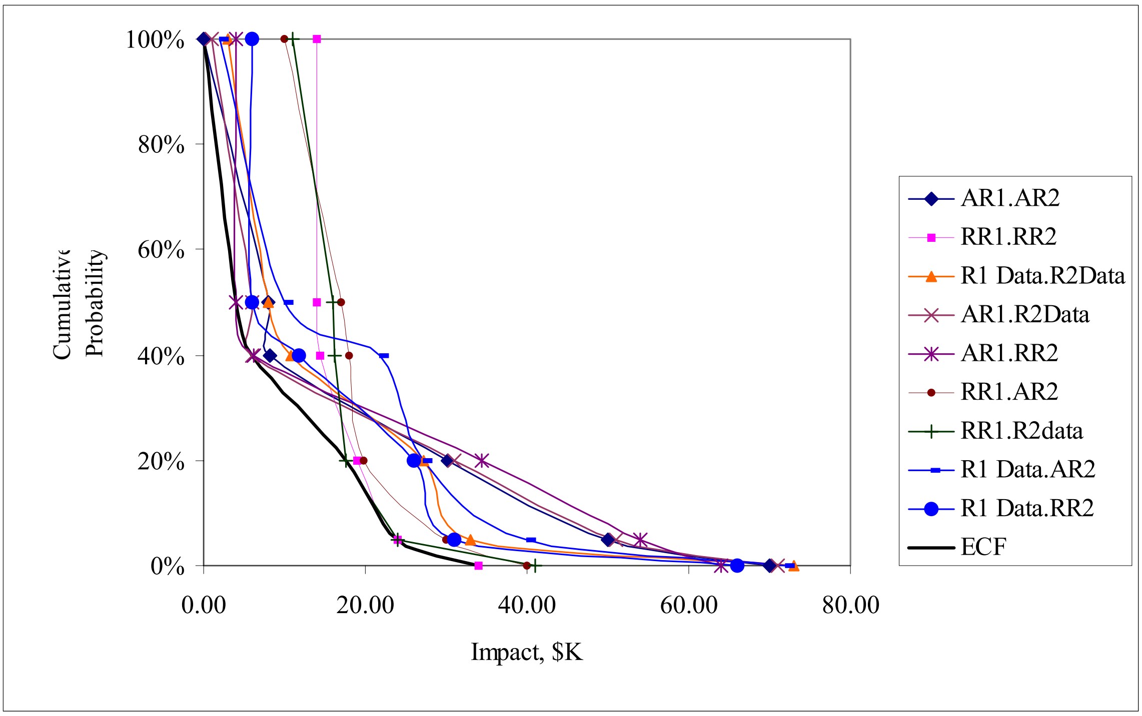


Figure 7. Cumulative risk profiles and ECF for the case of two risks

The following observations can be made based on Table I:

1. No TPRRA dominates for all possible outcomes. The composition of the efficient RRA set varies with the probability of success.
2. JR4 has the lowest mean value ($14.2K) and one of the largest standard deviation ($16.0K). Most project managers would not select it as the preferred option.
3. JR7 dominates for probabilities of success between 80% ($17.6K) and 95% ($24K).

4. JR2 dominates for probabilities of success greater than 95% and has an estimated maximum cost of \$34.0K.
5. The cost differentials among the different strategies are significant. For example, JR7 provides a 80% probability of success for \$17.6K while the corresponding cost with JR5 is \$34.4K. The cost-benefit of judicious risk management increases with increased probability of success.
6. Hybrid options such as JR7 are worth further consideration. Successful project managers often favor such options, where additional data is pursued for some of the risks.
7. For all of the above RRAs, the value given by the sum of the mean and standard deviation corresponds to approximately an 80% probability of success. We find this surprising because we do expect the CLT to be applicable under the assumed conditions. But this is also very interesting because it suggests that the closed form risk value approximation presented in Section 4 may have wider applicability than one might anticipate. The analysis may simplify as the risks increase in number.

In conclusion, the proposed approach is capable of providing much detailed and valuable information. But the models and input data depend on engineering judgement and we stress the need to use the analysis judiciously. The challenge is in modeling and quantifying the project risks and RRAs; the computations can be routinely performed using the commercially available software identified in Section 1.

5.2. Workflow for Determining the Efficient RRA Set and Optimal Contingency

Figure 8 depicts the workflow for the method developed in this paper. The associated activities can be categorized as follows:

1. Start with the criteria for selecting the RRAs. These may include an acceptable probability of success or Total Project Cost (TPC) and Confidence Level (CL). (Activity A0).
2. Identify, quantify, and prioritize all technical risks. (Activities A1 - A3).
3. Select risks for further analysis. (Activity A4).
4. Develop, model, and quantify the potential individual RRAs. (Activities A5 - A6).
5. Develop, model, and quantify the potential TPRRAs. (Activities A7 - A9).
6. Determine ETPRRAS, TPECF, and optimal TPCC. (Activities A10 - A11).

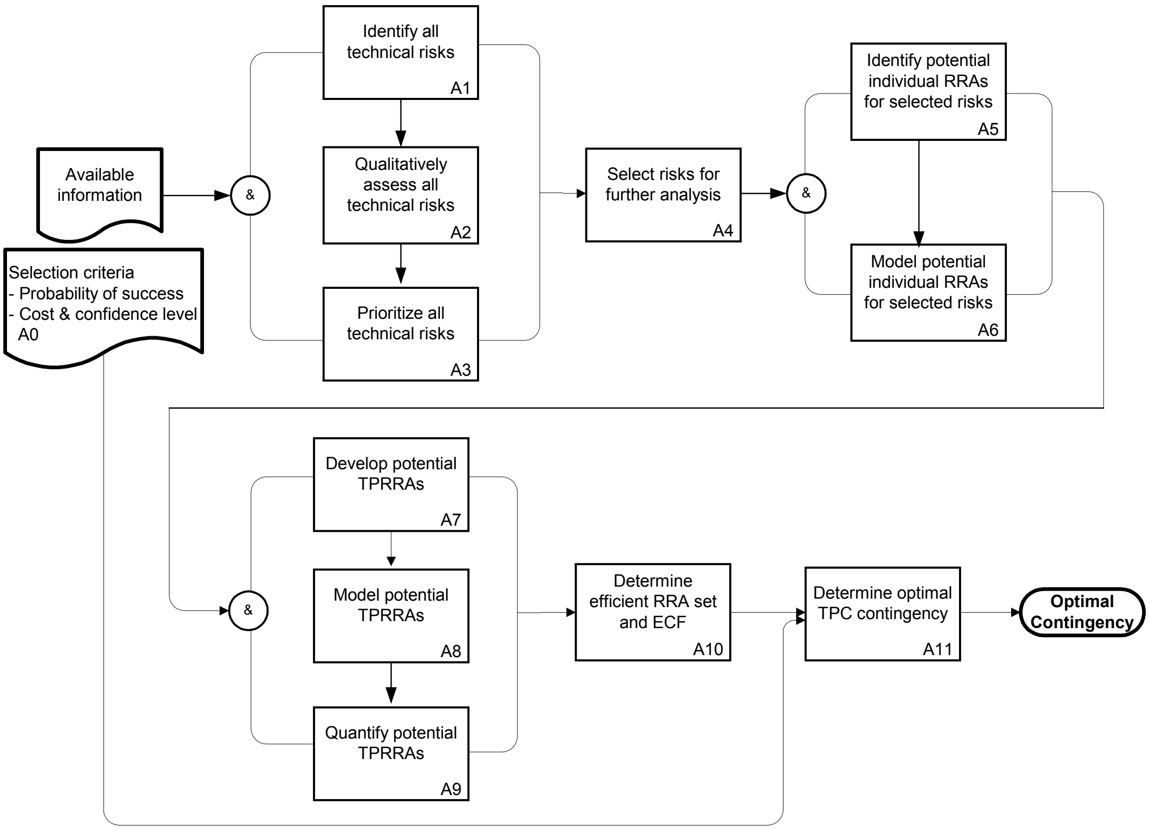


Figure 8. Workflow for determining efficient RRA set and optimal contingency

When first implementing the proposed approach, it is important to heed the following words:

- "… the more convenient, more natural set type of analysis is a logical first step in the formal analysis of portfolios." [Markowitz, 1976: 281]
- "After a point, complexity adds work without appreciably increasing the value of the analysis." [Markowitz, 1976: 101]

6. IMPLICATIONS FOR RISK AND CONTINGENCY MANAGEMENT

We have built on Markowitz' portfolio selection ideas [Markowitz, 1976] a systematic and practical approach for effectively managing project technical risks and achieve either (1) the highest probability of success for a given cost, or (2) achieve a given probability of success for the lowest cost contingency. It provides a framework for answering the following important risk management questions:

1. How much contingency should be available to insure the acceptable probability of success?
2. What set or combination of individual RRAs provides the acceptable probability of success for the lowest cost?
3. What are the risk profiles (probability Vs consequence) of the candidate TPRRAs?

The answers have significant implications for efficiently managing project risks and cost contingencies:

1. For every level of risk there is a combination of individual RRAs, the ETPRRAS, that provides the acceptable probability of success for the lowest cost. The composition of this set varies with probability and it defines the ECF or optimal total project contingency.
2. It is important to explicitly consider risk at the project-wide level. The total project efficient RRA set is not simply the combination of the individual efficient RRAs.
3. Selecting the total project efficient RRA set should be the primary objective of risk management. Higher risk should be viewed as a trade-off in trying to achieve a higher probability of project win and/or higher profit.
4. The mean and variance do not fully characterize risk, and their use may in some cases lead to wrong decisions. Decision-makers need additional data that provides greater visibility into the individual and total project risk profiles.
5. The ability to determine the ETPRRAS empowers the decision-maker to manage risk and thereby achieve the highest probability of success for a given contingency.
6. TPCC should be held centrally and managed at the project-wide level. This principle is essential to successfully manage the TPC [Kujawski, 2001]. Although it has not been explicitly identified in the analysis, it is an integral element of the proposed approach.

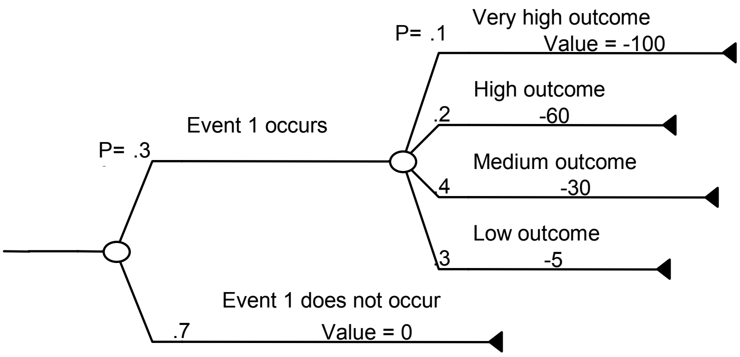
In conclusion, the proposed approach is based on powerful concepts that apply to areas beyond portfolio selection. For example, they have recently been extended to petroleum exploration and production [Ball and Savage, 1999]. The project manager who properly implements them is more likely to have a successful project at a lower cost. The challenges to the team are:

- Adequately identify and quantify all the risks.
- Identify and deal with potential sources of correlation among the risk elements.
- Develop and quantify the individual RRA options.
- Adopt the approach and associated thinking.
- Judiciously use the models.
- Treat risk management as an integral part of project management.

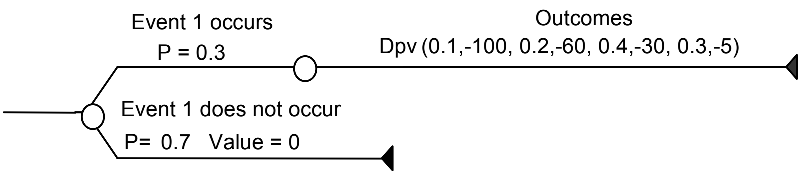
APPENDIX A: MODELING REPRESENTATIONS AND NOTATION

Figure 9 depicts the modeling representations discussed in Section 2:

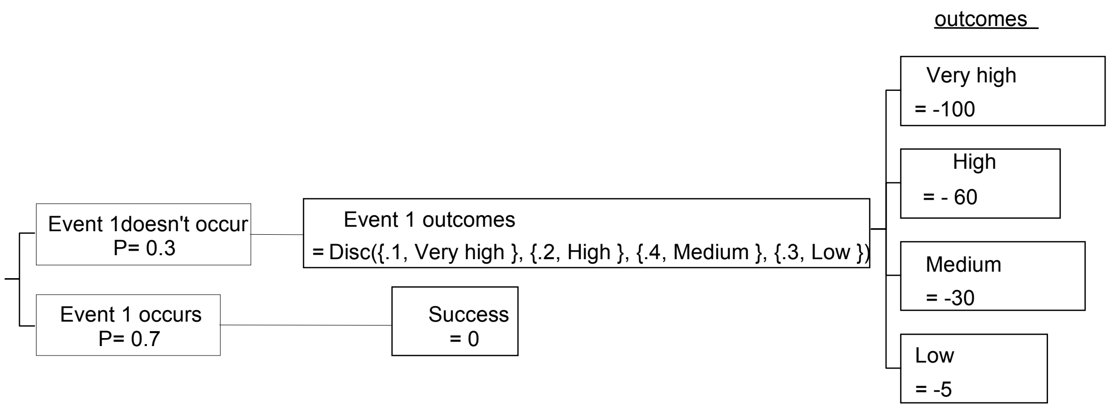
4. Figure 9a. Standard Event Tree (ET) with each branch representing an individual outcome.
5. Figure 9b. A probability distribution is associated with each branch in the ET. In the case shown, the single branch with the specified discrete distribution function replaces the top four branches in Figure 9a.
6. Figure 9c - The ET is explicitly modeled using specialized software such as DecisionPro® or a spreadsheet such as Excel®.



(a) Standard representation



(b) Representation using discrete distribution function



(c) Spreadsheet model

Figure 9. Example of an event tree using different representations

For completeness, we briefly summarize the information content of Figure 9.

1. The ET in Figure 9a has five possible outcomes indicated by the five end branches. These outcomes arise as follows:

a) "Event 1" has a 30% probability of occurring and a 70% probability of not occurring.
b) Given that "event 1" occurs there are four possible outcomes with the following conditional probabilities:

- 10% chance of a "Very high outcome" with a value -100
- 20% chance of a "High outcome" with a value -60
- 40% chance of a "Medium outcome" with a value -30
- 30% chance of a "Low outcome" with a value -5

2. The ET in Figure 9a is equivalent to the following discrete probability distribution:

Outcome	0	-5	-30	-60	-100
Probability	0.7	0.06	0.12	0.09	0.03

Note: The probability of each outcome is obtained by multiplying the probability that the event is realized by the conditional probability of the outcome given that event.

3. We denote the discrete distribution function with n possible outcomes with value V_i and probability P_i for outcome i by $Dpv(P_1, V_1, P_2, V_2, \ldots, P_n, V_n)$.

4. Use of the discrete distribution function provides a convenient representation of a chance node and its associated outcome branches, as shown in Figure 9b. It simplifies the ET (or DT) and provides a framework for modeling outcomes with continuous distributions.

5. ETs can also be modeled using a standard spreadsheet as shown in Figure 9c. Spreadsheet models combined with Monte Carlo simulation provide a convenient framework for dealing with complex trees where the values of branches are defined by probability distribution functions. The cells in Figure 9c contain formulas that are equivalent to the corresponding node and branch in the ET in Figure 9a.

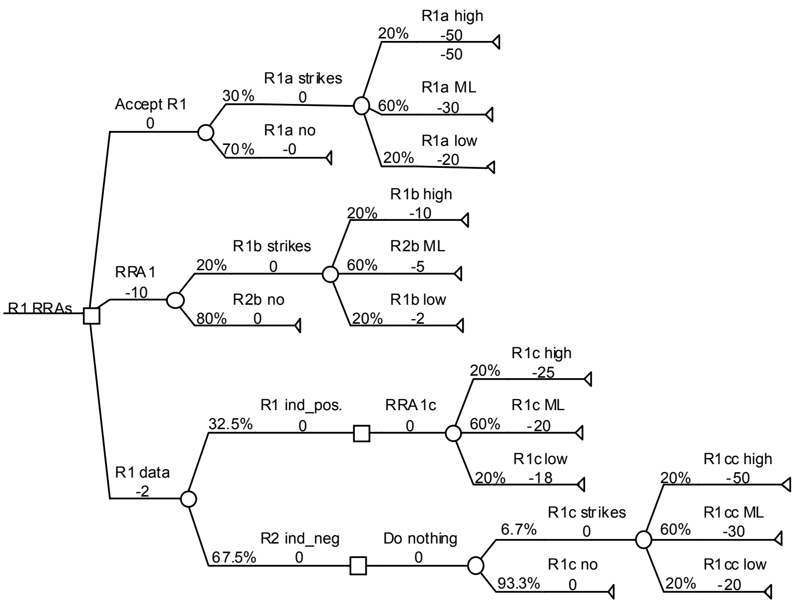
Commercially available software tools (DecisionPro®, PrecisionTree® with @Risk, Insight.xla®, Crystall Ball®, etc) can be used to assist in the development and analysis of the above risk models.

APPENDIX B: ADDITIONAL DATA FOR ILLUSTRATIVE EXAMPLES

B.1. R1 RRAS

B.1.1 Detailed RRA DT

Figure 10 depicts the standard DT representation for the R1 RRAs described in Section 3.



Outcomes

Prob.	Value
6%	-50
18%	-30
6%	-20
70%	0
4%	-20
12%	-15
4%	-12
80%	0
6.5%	-27
19.5%	-22
6.5%	-20
0.9%	-52
2.7%	-32
0.9%	-22
63.0%	-2

Figure 10. R1 RRAs, standard DT representation

Decision nodes and chance nodes are depicted as squares and circles, respectively. The branches that originate with decision nodes represent the available RRAs. The branches that originate with chance nodes represent the possible probabilistic outcomes. Each branch has a probability and cost value associated it. These values are conditional on the RRA. To differentiate among the three RRAs, we explicitly denote the associated risks as R1a, R1b, and R1c.

The probabilities of the outcomes associated with each RRA sum to 1. This is an important check on the validity of any RRA DT model. The three RRAs are mutually exclusive, and each has its own and independent existence. Decision nodes are deterministic; only one of RRAs gets implemented for each risk. Once a RRA is implemented, only the associated outcomes can be realized and the sum of their probabilities must equal 1. To characterize each RRA, the subtree associated with each RRA needs to be analyzed individually. As it should be, the risk profile and cumulative risk profile for each RRA are identical to those shown in Figures 3a and 3b, respectively.

B.1.2. Quantification of the "R1 data" RRA

As indicated in Section 3, the " R1data " RRA requires additional analysis beyond elicitation of the data from the domain experts. The domain experts normally have information on the prior probabilities of R1 and the effectiveness of the proposed testing and/or analysis. The data assumed for the "R1 data" RRA is shown in Figure 11a.

The events in Figure 11a, however, appear in the reverse order of the events in the tree in Figure 10. Bayes' Formula [Haimes, 1998] provides a tool to calculate the probabilities needed as input in Figure 10. The resulting analysis is presented in Figure 11b.

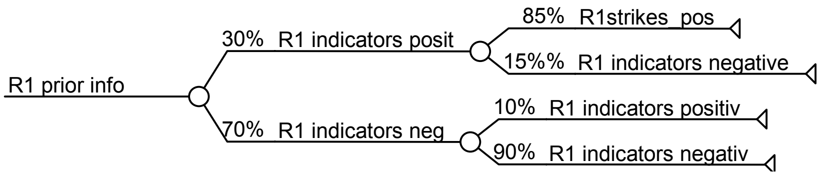


Figure 11a. Event tree based on prior information

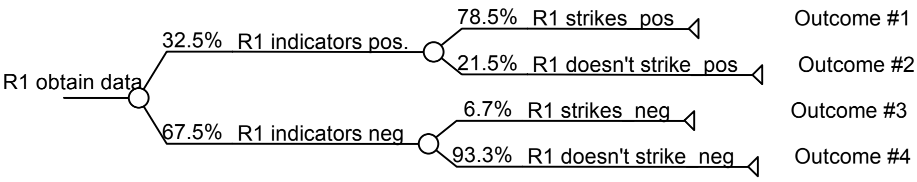


Figure 11b. "Reversed" event tree

The information obtained during the risk reduction phase may be erroneous and may result in any of the four outcomes shown in Figure 11.b. Note that the project team gets kudos only under outcome #4. Under outcome # 3, the team is blamed for inadequate risk management. Under outcomes #1 and #2, it is usually very difficult to convince management of the cost-benefit of the implemented RRAs.

B.2. R2 RRAs Data

The data for the R2 RRAs is summarized in the following Figures:
- Figure 12 depicts the quantified mathematical model
- Figure 13 compares the means and variances of the three RRAs
- Figure 14 depicts the cumulative risk profiles and the associated ECF.

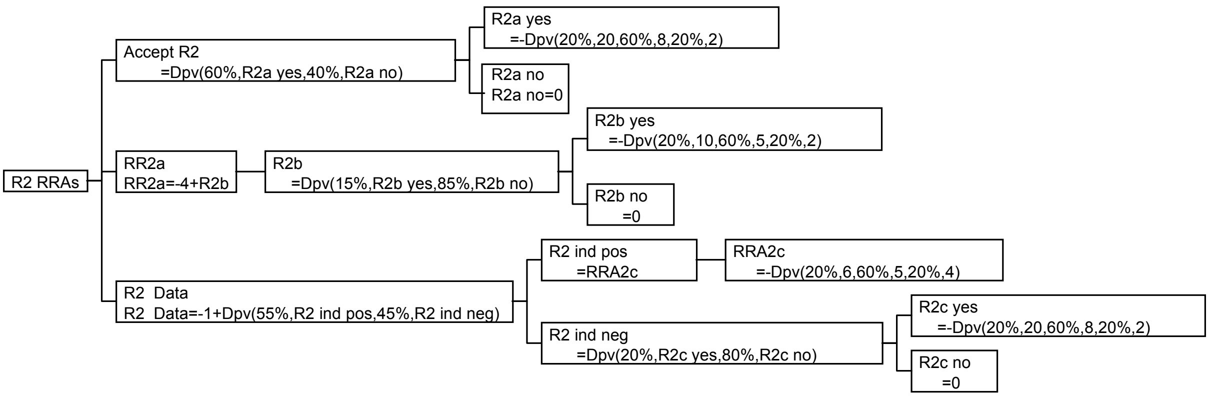


Figure 12. Quantified mathematical model for R2 RRAs

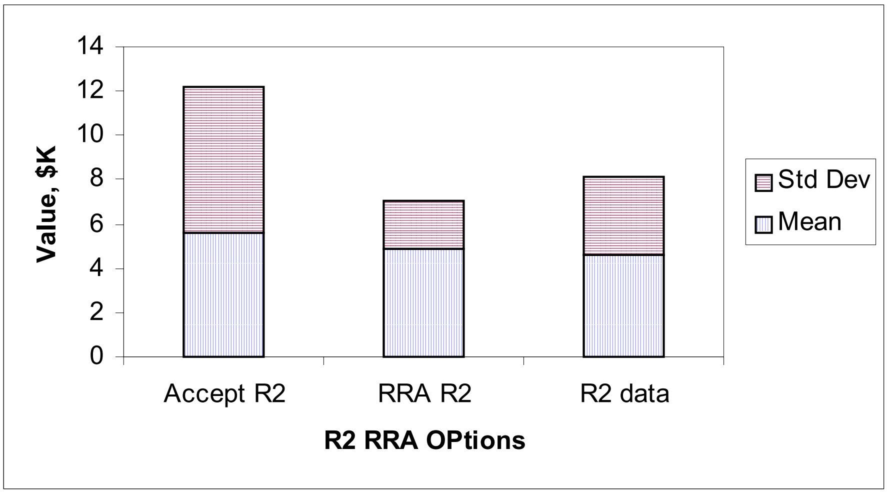


Figure 13. Means and standard deviations for R2 RRAs

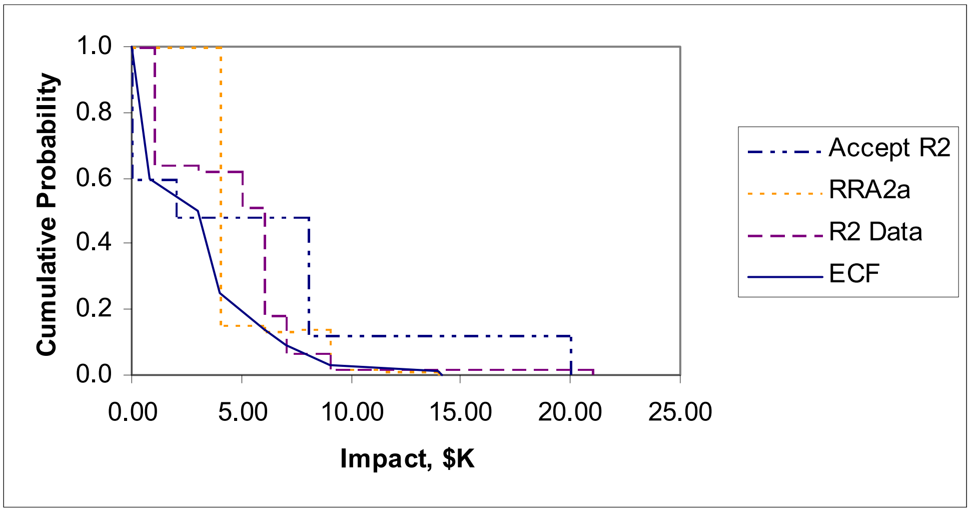


Figure 14. Cumulative risk profiles and ECF for R2 RRAs

APPENDIX C: DISCRETE PROBABILITY DISTRIBUTION CALCULUS

We revisit the example in Section 5 using the calculus of discrete probability distributions [Kaplan, 1981]. This approach is instructive and provides additional insight into the probabilistic summing of discrete risks. We detail the analysis of the joint RRA, (Accept R1 and Accept R2).

The joint RRA, (Accept R1and Accept R2), has 16 possible outcomes with probabilities and values given by:

$$\text{(Accept R1 and Accept R2)} = \{(Pi(1), Vi(1)) + (Pj(2), Vj(2))\}$$
$$= \{Pi(1)*Pj(2), Vi(1) + Vj(2)\}$$

i =1, 4 j =1,4 corresponding to the 4 possible individual outcomes (High, ML, Low, None).

Table II provides the resulting risk profile.

Table II. Risk Profile for Joint RRA, (Accept R1 and Accept R2)

	R1 no	R1 low	R1 ML	R1 high
R2 no	(28%, 0)*	(2%, -20)	(7%, -30)	(2%, -50)
R2 low	(8%, -2)	(1%, -22)	(2%, -32)	(1%, -52)
R2 ML	(25%, -8)	(2%, -28)	(6%, -38)	(2%, -58)
R2 high	(8%, -20)	(1%, -40)	(2%, -50)	(1%, -70)
*(Probability, Value $K)				

REFERENCES

B.C. Ball and S.L. Savage, Notes on Exploration and Production Portfolio Optimization, Ball & Savage Associates, 1999.
C. Chapman and S. Ward, Project Risk Management - Processes, Techniques and Insights, Wiley, Chichester, 1997.
C.B. Chapman, S.C. Ward, and J.A. Bennell, Incorporating uncertainty in competitive bidding, International Journal of Project Management 18 (2000), 337-347.
Crystal Ball, Decisioneering, http://www.decisioneering.com/
Decision Pro 3.0, Vanguard Software Corporation, http://www.vanguardsw.com.
R.L. Dillon and M.E. Paté-Cornell, APRAM: An Advanced Programmatic Risk Analysis Method, International Journal of Technology, Policy and Management, Vol.1, No.1, (2001), 47-65.
D. Hillson, Developing effective risk responses, Proceedings of the 30th Annual Project Management Institute 1999 Seminars & Symposium.
D. Kahneman, P. Slovic, and, A. Tversky, Eds., Judgement under uncertainty: Heuristics and biases, Cambridge University Press, Cambridge, 1999.
S. Kaplan, On The Method of Discrete Probability Distributions in Risk and Reliability Calculations - Application to Seismic Risk assessment, Risk Analysis 1 (1981), 189-196.
P.R. Garvey, Probability Methods for Cost Uncertainty Analysis: A Systems Engineering Perspective, Dekker, New York, 2000.
D.R. Graham and J. Dechoretz, The Cost-Identification & Management System (CRIMS), AF/SMC, 1995, http://web.deskbook.osd.mil/valhtml/2/2B/2B4/2B4S08.htm
Y.Y. Haimes, Risk Modeling, Assessment, and Management, Wiley, New York, 1998.
E.M. Hall, Managing Risk: Methods for Software Systems Development, Addison-Wesley, Reading, 1998.
Insight.xla, Business Analysis Software for Microsoft Excel, Duxbury Press, Pacific Grove, 1998, http://www.stanford.edu/~savage/.
E. Kujawski, Why Projects Often Fail Even With High Cost-Contingencies, submiited to Systems Engineering, 2001.
H.M. Markowitz, Portfolio Selection: Efficient Diversification of Investments, Yale University Press, New Haven, 1976.
S.R. Moran, Cost-Risk Analysis - The Devil Is In The Details, Space Systems Cost Analysis Group (SSCAG) Meeting, January 1999.
@Risk and PrecisionTree, Palisade Corporation, http://www.palisade.com.
E. Schragenheim and H.W. Dettmer, Does Your Internal Management Meet Expectations?, CrossTalk 14 (2001) 19-25.
M.A. Shaikh, Project Schedule Recomputation after Risk Inclusion, Systems Engineering 1 (1998), 242-249.
Z. Shapira, Risk Taking - A Managerial Perspective, Russell Sage Foundation, New York, 1995.
U.S. Department of Defense, Joint Industry/Government Parametric Estimating Handbook, 1999.
U.S. Department of Energy, Project Management Practices, Practices 8 and 12, Draft, October 2000.
S.R. Watson and D.M. Buede, Decision Synthesis - The principles and practice of decision analysis, Cambridge University Press, Cambridge, 1987.